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TITLE

A Physiological Data Analysis Toolbox for the Analysis of Acceleration Data

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A PHYSIOLOGICAL DATA ANALYSIS TOOLBOX FOR THE ANALYSIS OF ACCELERATION DATA

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1. SUMMARY

As an alternative to using traditional first principle-based modeling of a protected subject's physiological responses to real-life acceleration trains (both positive and negative-to-positive Gz transitions), a nontraditional systematic approach is being designed to facilitate the evaluation and prediction of human cardiovascular responses to G-suit and Positive Pressure Breathing (PPB) pressure schedules. The purpose of this work is to develop novel improved Anti-G protection schedules optimized for individual pilots in general and push-pull protection in particular. The proposed nontraditional systematic models are based on input-output relationships supplemented by expert knowledge. Therefore, both the experimental design and physiological data processing architecture are critical in this project. Six subjects (two females and four males) participated in the initial experimental effort. Persistently excited non-linear G-suit and PPB pressure schedules, which are not direct linear functions of Gz levels, have been applied using two types of electronic valves: (i) a combined Breathing Regulator and Anti-G valve (BRAG valve)[1]; and (ii) two custom-designed electronic (SAMCAV)[2] valves. The recorded parameters were heart-level blood pressure, ECG, respiratory rate, G-suit and PPB pressures. Among other issues, this paper describes a Physiological Data Analysis Toolbox (Φ-DAT) that integrates statistical, fuzzy and linear trend investigations with higher-order spectrum analysis of the experimental data. Φ-DAT has been designed as a preprocessor of the nontraditional systematic modeling architecture and proven very efficient in establishing correlation and trend dependencies between the non-linear pressure schedules employed and responses obtained.

2. INTRODUCTION

Currently, the pressurization of anti-G-suits and positive pressure breathing (PPB) is controlled by mechanical valves that generate pressure schedules linearly dependent on momentary acceleration measurements. However, the physiological responses to acceleration trains and pressure schedules are non-linear due to time delays and complex reflex functions of the cardiovascular dynamics. Using modern microprocessor-controlled electronic valves and fast computer technologies, this project is aimed at the development of an Expert System for offline and online adaptive generation and control of Anti-G counter-measures optimized for individual pilots and groups of pilots. To develop such an Expert System, there is a need to model and predict the physiological responses of individual subjects to candidate non-linear schedules of G-suit pressure and PPB. The nontraditional systematic modeling and prediction architecture is being developed mainly based on input-output experimental relationships and, therefore, both the experimental design and physiological data processing architectures are critical. It is typically not obvious how to design acceleration experiments so that maximum amount of information on the cardiovascular dynamics is obtained using a limited number of expensive manned experiments. This paper addresses the design of such experiments, as well as a systematic approach to analyzing the experimental data.

3. METHODS

3.1 Subjects

Six subjects (two females and four males) with the mean age of 35 ± 3.7 years, height of 171.9 ± 11.5 cm, and weight of 73.1 ± 16.0 Kg participated in the study. All subjects were members of DCIEM Acceleration Team and passed DCIEM medical examinations that included a full cardiovascular test required by the Human Subjects Ethics Committee for participation in G-suit and PPB studies. Three different sizes of STING[3] suit (small, medium, and large) were used to ensure proper individual fit.

3.2 Experimental Setup and Protocol

Figure 1 shows the experimental setup for both BRAG and SAMCAV valves. For the BRAG valve, the PPB outlet pressure was a function of G-suit pressure. To achieve independent control of G-suit and PPB, two SAMCAV valves were used to control the G-suit and PPB pressure individually. In general, the experiment was designed for three different system configurations: (i) G-suit without PPB (SAMCAV valve) with pressures varying from 2 to 8 psi and onset rates of 0.4 to 3 psi/sec; (ii) G-suit with PPB (SAMCAV valves) with pressures varying from 2 to 8 psi for G-suit and 0 to 60 mmHg for PPB; and (iii) G-suit with PPB (BRAG valve) with pressures varying from 2 to 8.8 psi and the corresponding PPB varying from 0 to 51

[1] "Combined regulator and Anti-G valve" designed by Normalair-Garrett Ltd. (NGL).

[2] "Computer-controlled valve" designed by ESI in co-operation with DCIEM.

[3] Sustained Tolerance INcreased G (STING).

"*conditional*" and "*unconditional*" outputs were compared to check their effect on the inputs. Observations of mean values can provide information on the significance and type of a model dependency on its input variables. The *t*-statistic has also been used for testing the null hypothesis [10, 11].

Auto-correlation and cross-correlation

The primary purpose of linear correlation analysis is to measure the strength of a linear relationship between two variables. This tool can also be used in designing experiments. The quantitative information contained in the correlation plots can be used at the modeling stage. Initially, it is not generally clear what type of model may be appropriate for a batch of data. The shape of the auto-correlation plot can be used for preliminary analysis of this issue. In general, the shape of the auto-correlation function reveals the properties and order of the process [5]. Moreover, it can be used to evaluate whether the input variables (G-suit and PPB pressures) have been varied independently.

Higher order spectral analysis

Auto-correlation and power spectrum analysis cannot reveal all the information contained in a stochastic non-Gaussian or deterministic signal. Higher-order spectra analysis looks into the higher-order momenta or cumulants of a signal. The Higher-Order Spectral Analysis (HOSA) Toolbox [12] is implemented in Φ-DAT for this purpose.

In addition to generating the pertinent analyses described above, Φ-DAT generates an output (report) file that contains the relevant parameters and calculated indices for the data being analyzed. The output file is used for proper clustering the experimental results in a database and further non-traditional modeling (system identification), prediction, and generation of optimal Anti-G protections by the Expert System mentioned in Section 2.

6. DESIGN OF EXPERIMENTS

6.1 Design of Inputs

The performance of the input pressure profiles designed for this study was evaluated using the correlation analysis. The results (Figures 5-8) indicate a high degree of correlation between inputs (G-suit and PPB pressures) and outputs (systolic and diastolic blood pressures). Figures 5 and 6 show the correlation analysis results for G-suit, and G-suit with PPB in the experiments with subject No.1 (dubbed "S1"), respectively. The correlation analysis results for the BRAG valve are shown in Figure 7. It should be mentioned for the case of the BRAG valve that G-suit and PPB pressures are linearly dependent. This dependency between G-suit and PPB pressures is not desirable in the comprehensive model identification process.

Figure 8 shows the correlation results for a group of five subjects. It can be noticed again that the inputs and outputs are highly correlated. Moreover, it has been found in our work [13] that the random pressure profile resulted in a very comprehensive model for the case of G-suit and PPB applied together. To develop a comprehensive model for the case of G-suit and PPB applied independently, there is a need of more experiments with different levels of PPB combined with randomly changing G-suit pressure (that is, uncorrelated G-suit and PPB pressures) [13]. In conclusion, from the point of view of the experimental design, the correlation analysis can be used for evaluating the input signals designed, such as G-suit and PPB pressure profiles.

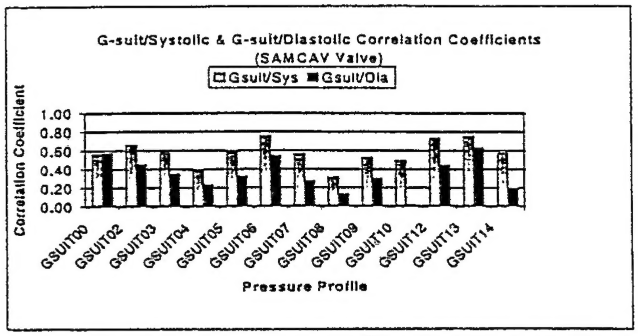

Figure 5. Correlation coefficients for S1: Gsuit with SAMCAV valve

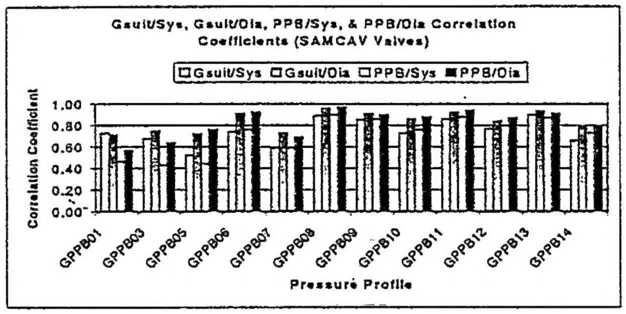

Figure 6. Correlation coefficients for S1: Gsuit and PPB with SAMCAV valves

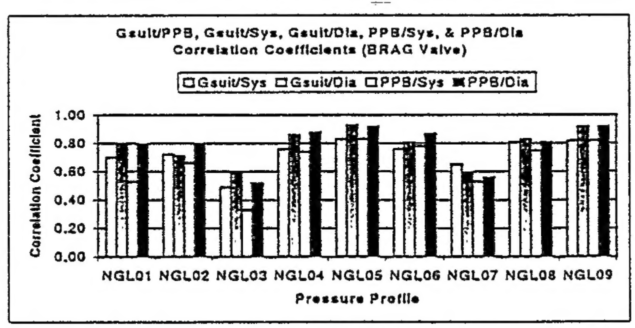

Figure 7. Correlation coefficients for S1: Gsuit and PPB with BRAG valve

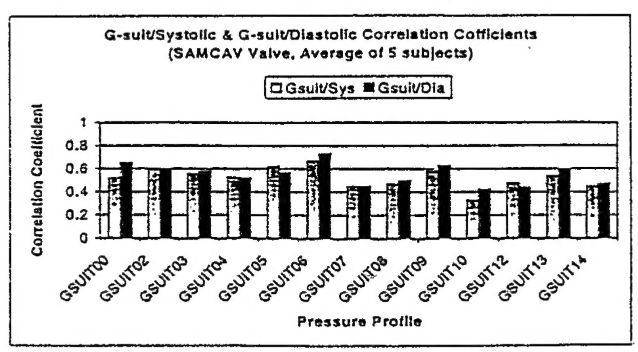

Figure 8. Correlation coefficients for five subjects - Gsuit and SAMCAV valves

Table 3. Conditional and unconditional standard deviations of heartbeat rate

Pres. Profile Unconditional		Conditional, Heartbeat Rate (bpm) L1	L2	L3	L4	L5	L6	L7	L8
Profile	σ	σ 1	σ 2	σ 3	σ 4	σ 5	σ 6	σ 7	σ 8
S1gsuit00	3.5	2.4	2.7						
S1gsuit01	7.2	7.2	4.3						
S1gsuit02	7.0	4.9	4.2	3.7	7.1	5.1	6.1	6.3	5.7
S1gsuit03	8.2	6.1	6.5	6.4	5.6	8.2			
S1gsuit04	8.1	4.2	6.6						
S1gsuit06	11.	5.7	8.7						
S1gsuit13	7.0	2.6	2.0	3.0	1.6				
S1gppb03	14.	7.8	15.	12.	7.1	16.			
S1gppb05	16.	12.	15.	16.	16.	12.			
S1gppb07	13.	4.1	12.						
S1gppb14	7.7	7.9	7.6						

It is shown in Tables 1-3 that the criteria of having the smaller standard deviation for the conditional population than for the unconditional one is satisfied in most of the cases considered. This comparison also reveals the quality of the experiment conducted. Moreover, observation of the mean values can reveal important information on the effect and relationship of input to the output.

A t-statistics test [10, 11] with 95% confidence level has been performed on the conditional population to find out whether the input is capable of explaining the output variation. Table 4 shows the result of the t-test for subject "S1" with a multi-step G-suit pressure input. The quantifier '1' in Table 4 indicates that the variation in output is due to the input, which corresponds to the rejection of null hypothesis [10], and 0 states that the input cannot explain the output variation, which means the acceptance of null hypothesis. This is preliminary step can be used for eliminating the unacceptable data. It also shows the performance (effectiveness) of the designed inputs.

Figures 12-14 show the conditional means trends for systolic and diastolic blood pressures, and heartbeat rate for subject "S1." It can be seen from the figures that there exists a linear trend for systolic and diastolic blood pressure. This is not valid for the case of heartbeat rate. In general, the trend analysis technique reveals information about the input/output relationship. This relationship can be linear or non-linear. However, a non-linear relationship can be approximated by a higher-order polynomial. It should be mentioned that we are interested in the dynamic relationship between input and outputs over a time period.

Table 4. T-test results

S1Gsuit02	L1	L2	L3	L4	L5	L6	L7	L8
Ho (Sys)	1	1	0	1	1	1	1	1
Ho (Dia)	1	1	1	1	1	1	1	1
Ho (Hb)	1	1	1	1	1	1	1	1

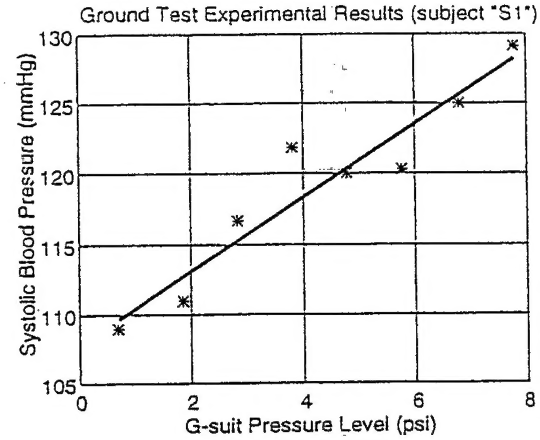

Figure 12. Conditional means for experiment S1Gsuit02 (Systolic blood pressure)

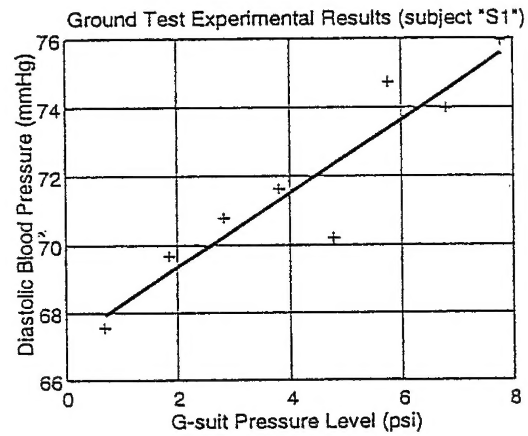

Figure 13. Conditional means for experiment S1Gsuit02 (Diastolic blood pressure)

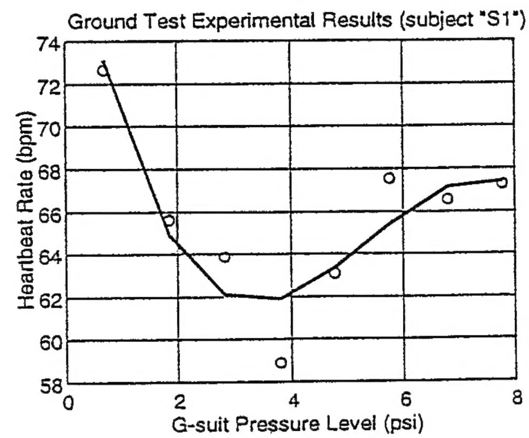

Figure 14. Conditional means for experiment S1Gsuit02 (Heartbeat rate)

6.4 Joint distribution, trend analysis, and hysteresis plots

To study the dynamics of input/output signals, it is necessary to investigate the qualitative behavior of the signals. Scatter diagrams (joint distribution plots) of input/output and output/output signals reveal qualitative

information about the structure of input/output dependency (e.g., linearity or non-linearity). A plot of the input or output signal versus an (input or output) signal delayed by time τ will show the degree of dependency of each present value of the signal on: (i) the previous values of its own states, such as the relationship of **output** to (**output-** τ **delays**); and (ii) the other signals, such as the relationship of **output** to (**input-** τ **delays**). The qualitative information contained in these plots can be used in system modeling. Also, the trend analysis can be used to define a quantitative approach for analyzing the scatter plots. Figures 15-17 show the joint distribution for the case of input (delayed) versus output (delayed) and output (delayed) versus output (current).

Two different types of trend analysis (fuzzy trend and linear trend) have been considered in the investigation of the nature of relationship between delayed input and output. The trend analysis can be used to determine [9]:

⇒ whether there exists a trend of increase in means as the level of the independent variable increases. The existence of this trend would correspond to the linear input/output relationship; or

⇒ whether the function which relates the means and the level of the independent variable is significantly curved. This would correspond to a non-linear input/output relationship.

The F-test statistics is used to investigate this type of dependency (e.g., linear or non-linear). It has been proved in [9] that the ratio of fitting curve mean square to its group mean square (F-ratio) has a so-called F-distribution. This means that if the F-ratio is high, the corresponding type of relationship exists between an input and output. For example, Table 5 shows the F-ratio results for the subject "S1" (the case of random G-suit profiles).

Table 5. F-ratios

Type of relation	Linear	Quadratic	Cubic
Systolic	72.10	0.13	1.20
Diastolic	83.50	4.70	0.62
Heart rate	50.10	7.70	2.50

It is clear from the F-ratio results (Table 5) that only the linear component of systolic and diastolic blood pressures, and linear and quadratic components of heartbeat rate are significant. Using this unique feature of F-ratio, it is possible to group the collected data into different groups. Also, the idea behind the fuzzy trend analysis is to define a number (fuzzy index) for comparing the qualitative results of the trend and scatter plot analysis.

Finally, a hysteresis plot has been defined for qualitative analysis of input/output data. Figures 18 and 19 show examples of such plots. The X-axis of the plot is either G-suit or PPB pressure. A physiological signal (e.g., systolic blood pressure) normalized by the G-suit or PPB pressure is plotted as the Y-axis. In general, the narrower the plot, the more repeatable the physiological response.

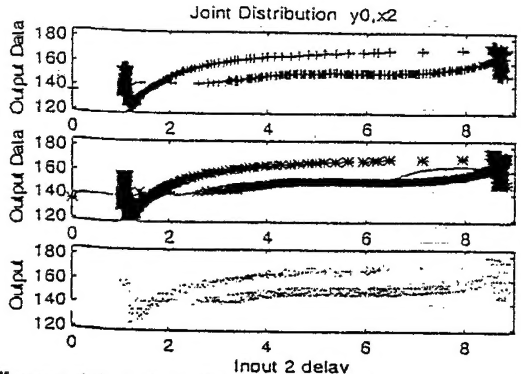

Figure 15. Joint distribution (phase portrait) for output versus (input-2 delays)

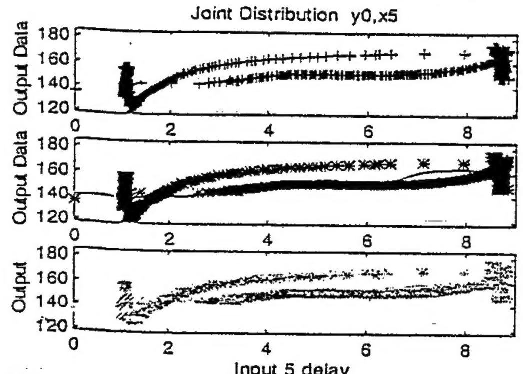

Figure 16. Joint distribution for output versus (input- 5 delays)

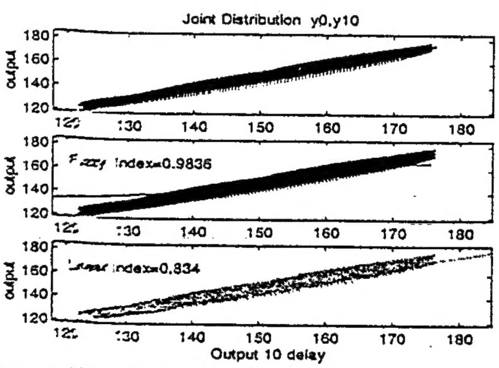

Figure 17. Joint distribution for output versus (output-10 delays)

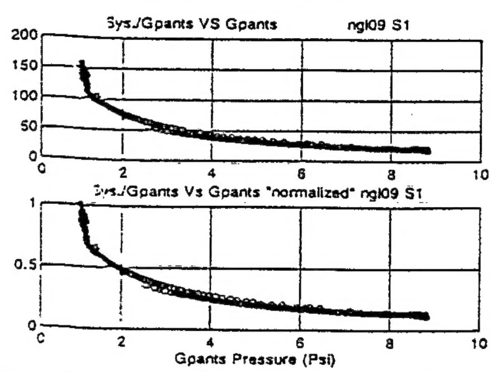

Figure 18. Hysteresis plot for Systolic blood pressure normalized by G-suit pressure

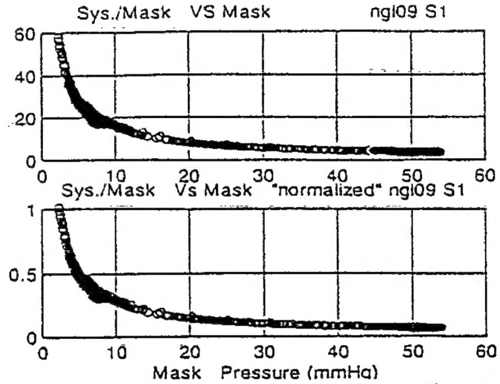

Figure 19. Hysteresis plot for Systolic blood pressure normalized by PPB pressure

6.5 Auto-correlation and Cross-correlation

The primary purpose of linear correlation analysis is to measure the strength of a linear relationship between two variables. This tool can also be used in the design of an experiment. In general, the trend analysis reveals the existence of a linear or non-linear relationship between the input/output signals. In the physiological systems, the maximum value in correlation analysis indicates the maximum dependency between input/output data in the case of linear relationship. Also, the sign and position of the maximum show the direction of relationship and lag or lead of the system, respectively. Therefore, the correlation analysis is a tool for obtaining more information about the characteristics of the system. Finally, it should be mentioned that the correlation analysis is very sensitive to the interval (sampling rate) of the data set. To eliminate this dependency, the bootstrap technique is typically used [10]. Figures 20-22 show the auto-correlation and cross-correlation for the case of a BRAG valve (NGL09) experiment. It has been mentioned earlier that the G-suit and PPB pressures are linearly dependent for the BRAG valve results.

6.6 Higher Order Spectral Analysis

Auto-correlation and power spectrum analysis cannot reveal all the information contained in a stochastic or deterministic signal. Higher-order spectral analysis looks into the higher-order momenta or cumulants of a signal to find out more information about the process. This feature has not yet been fully implemented for the analysis of the ground-test experimental data.

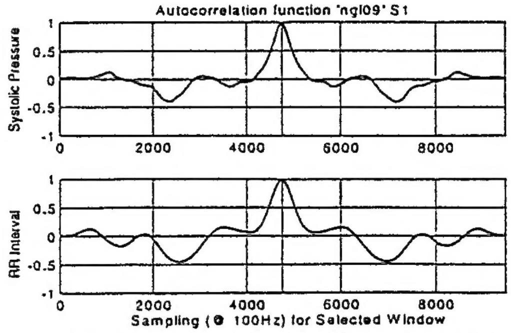

Figure 20. Auto-correlation (Sys. & RR interval)

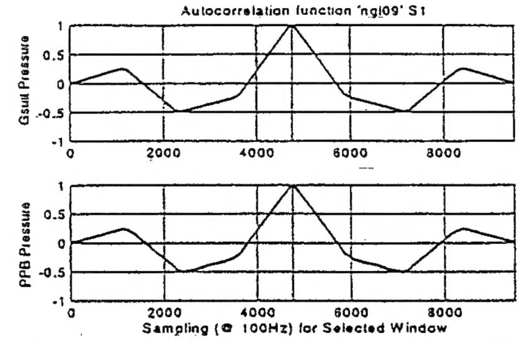

Figure 21. Auto-correlation (G-suit & PPB)

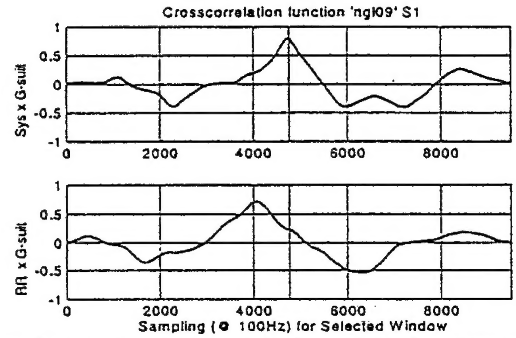

Figure 22. Cross-correlation (G-suit versus Sys. and G-suit versus RR interval)

7. CONCLUSIONS

A generic toolbox has been developed for analyzing the results collected in physiological experiments aimed at the development of advanced non-linear Anti-G countermeasures. The toolbox called **Physiological Data Analysis Toolbox (Φ-DAT)** has been applied to the analysis of physiological data collected in Gz experiments. This tool can be also used at the experiment design stage. If Φ-DAT is used for the preliminary analysis of physiological data, it yields important information that can be further used at the modeling stage [5]. Finally, it should be mentioned that Φ-DAT toolbox can be used to analysis different types of physiological experimental data.

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